# Energy-Conscious Mobility Solutions for Drone-Based Internet Access

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#### **Abstract**

Drones (UAVs) have outstanding capability for remotely providing internet services to hard-to-reach places as well as to areas affected by disasters. This paper presents a novel approach that focuses on energy efficiency for mobility frameworks in drone internet access systems by optimizing flight path scheduling to achieve maximum coverage and minimal energy expenditure. The framework achieved enhanced reliability in coverage and significant energy savings compared to conventional UAV deployments, as demonstrated in simulations and case studies conducted within the context of a flood-related emergency. Dynamic reallocation strategies for maintenance in challenging operating environments are also discussed, along with practical considerations for large-scale deployment. These results highlight the advanced intelligent UAV networks' ability to overcome the difficulties of maintaining resilient and dependable wireless communication services in emergencies and underserved areas.

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## 1 Introduction

Although there have been developments in global internet usage, many billions of people in rural, remote, and disaster-prone areas still struggle to access reliable internet connections (Canton, 2021). Things like fiber-optic cables are too expensive and physically challenging to install in these regions. Drones may be able to help with the challenge of providing supplementary wireless access in these areas (Akyildiz & Kak, 2019).

Researchers from both industry and academia have focused on—or are in the process of focusing on—UAVs and their functions within dynamic networking environments. This includes aerial base stations (ABS), relay nodes, and data collection platforms. Drones have proven their worth in terms of mobility (Mozaffari et al., 2019). Not only are they capable of moving around freely, but they can also do so while communicating with the base and gaining (in terms of coverage) optimal visibility/camera angles.

Currently, research on drones used in multi-drone missions, long-range remote-controlled operations, and energy grid and network control systems has not been focused explicitly on drones (Zeng et al., 2016). The choice of maneuvering height, speed, and rotation angles that such missions demand depends on the strategic choice of these factors, which is dramatic in terms of energy needs and network accessibility. (Fotouhi et al., 2019). Items which can be directly controlled are to set limits to devices and signal command signals through programmable control graphics processing units (GPUs). As well, the possibility to get rid of all non-active cubes in non-functional levels without much effort has a potent effect on redundancy loss and efficiency of the mission. First of all, the system is concerned with border patrols and surveillance (Shetty & Nair, 2024).

The energy models related to UAVs typically include elements such as flight dynamics, environmental effects (e.g., wind and terrain), and battery discharge characteristics (Pragadeswaran et al., 2024). There are heterogeneous mobility strategies, ranging from static hovering to dynamic trajectory optimization that employ heuristics or machine learning techniques to minimize energy expenditure while maintaining relevance to service quality (Lyu et al., 2016). Most studies, however, tend to overlook practical constraints or fail to incorporate real energy versus performance metrics in their comprehensive simulations.

This paper introduces a mobility framework with energy optimizations for drones that serve as Internet access points by optimizing communication and trajectory planning alongside energy conservation. The specific objectives targeted in this work are:

- An energy-aware component, Drone-Assisted Network operational level architecture. This is focused on energy-sensing components.
- A mobility model with dynamic adjustment to energy constraints and user density.
- Performance evaluation simulation and case study analyses in metropolitan and rural areas.

The research contributes to the literature on the design space of sustainable UAV-based communication systems, considering the implications of developments in emergency response, remote learning, and rural development programs.

The remainder of this paper is structured as follows. Section 2 discusses the entire system framework, highlighting the features of the drone-based internet access network design. In Section 3, we explain the

proposed energy-aware mobility model with an emphasis on route optimization and energy expenditure management. In Section 4, we define the simulation setup, including environment, parameters, and evaluation test scenarios. In Section 5, we discuss and examine the results, with a particular focus on the system's energization and network functionality. Section 6 presents case studies to illustrate practical implementations. Lastly, Section 7 presents the final insights of the paper and offers recommendations for future work to be undertaken based on the findings of this study.

## 2 System Architecture and Design

Having a reliable architectural framework Figure 1 is of pivotal significance when providing internet access via drones in an efficient manner (Sharma et al., 2019). The proposed design incorporates energy optimized aerial movement and rapid wireless interfacing to aid users in isolated and hard to reach regions. The architecture is structured in three main components: the ground user tier, the UAV communication tier, and the backhaul tier. The integration of these tiers results in a system that is homogeneous, yet flexible, and readily adaptable for different deployments (Kalantari et al., 2017).

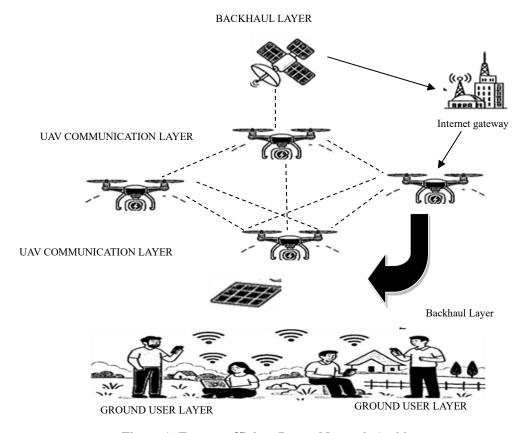


Figure 1: Energy-efficient Drone Network Architecture

The first tier, referred to as "ground user tier", comprises users or devices located in rural or remotely isolated regions (Hassija et al., 2021). These users access the system via standard wireless protocols, be it Wi-Fi or LTE, for the UAV communication modules. Because users do not require specialized devices, the system's coverage is greatly expanded. This characteristic simplifies system deployment in areas with limited resources.

The UAV communication layer represents the heart of the system. It includes multiple drones, each outfitted with GPS, communication systems, energy monitoring devices, and elementary computing

units (Aram et al., 2015). The drones set up an ad-hoc mesh network base station, which can configure itself depending on user needs, environmental factors, or even system malfunctions. The drones seamlessly and cooperatively ensure optimal connectivity and coverage and can act as either flying base stations or relay nodes (Alzenad et al., 2017).

This is followed by the backhaul layer, which focuses on maintaining upstream and downstream internet access. In extremely remote areas, this layer can utilize satellite connections or link up to terrestrial base stations and mobile edge computing (MEC) nodes when available. Some high-end drones (Liu et al., 2019) may be equipped with onboard MEC modules, which enable data to be processed locally, thus decreasing latency and part severe communications, and reducing the workload on the core server.

Each UAV manages several functional modules for integrating aerial networking, which increases the complexity. Based on signal strength, user positions, battery level, and other factors, the Mobility Control Unit governs flight behavior by optimizing paths and hovering locations. The Energy Monitoring System tracks both real-time power consumption and future energy needs. The Communication Manager ensures data routing and user access for proper bandwidth usage. Repositioning, recharging, and load redistribution are some of the tasks that a Task Scheduler dynamically prioritizes (Pragadeswaran et al., 2024).

The architecture supports a broad spectrum of deployment scenarios. The rapid deployment of drones for disaster recovery helps restore connectivity in areas where ground infrastructure has been severely damaged. In rural locations that are beyond the reach of conventional broadband, the system can provide continuous and scheduled internet service. Drones also offer temporary, high-capacity internet coverage for large-scale, short-duration events, eliminating the need for additional infrastructure (Lyu et al., 2016).

Key design considerations encompass scalability, which allows the entire system to increase or decrease in response to demand; inter-UAV coordination, which enables UAVs to evade redundancy and enhance their efficiency (Zhan et al., 2017); and load balancing, or the distribution of traffic and energy among the UAV fleet. Moreover, communication pathways redundancy allows for reliable fault tolerance alongside energy prediction systems, meaning dependable performance is upheld in cases of drone failure.

# 3 Energy-Conscious Mobility Model

The energy efficiency is one of the most critical attributes of drone-based communication systems since the battery capacity of Unmanned Aerial Vehicles (UAVs) is relatively small. The drone mobility should be strategized to balance the energy usage and regular user coverage.

#### 3.1 Energy Consumption Components

The energy consumption of a UAV entails multiple functions: propulsion, communication, and computation. Of these three, propulsion consumes the highest share of energy, usually between 80% and 90%. Some of the important Fuel Flow factors for propulsion energy consumption are the weight of the drone, the duration of hovering, the altitude and the wind energy. While Communication energy is small compared to the other functions, in some cases of communication with high data rates, it is a communication endurance problem. Onboard computation consumes energy too, especially in UAVs which are required to do local data processing or autonomous decision making (Zeng et al., 2016).

#### 3.2 Trajectory Optimization

To reduce energy consumption, UAV flight paths must avoid redundant motion and inefficient hovering. The proposed mobility model incorporates a cost-based trajectory planner that minimizes total energy use by calculating optimal routes between user clusters. The energy cost function considers propulsion, communication, and computational loads as (1):

$$E_{total} = \alpha E_{propulsion} + \beta E_{communication} + \gamma E_{computation}$$
 (1)

Where  $\alpha$ ,  $\beta$ ,  $\gamma$  are weighting factors that reflect the energy priority of each component (Sharma & Maurya, 2024). This optimization problem is solved using a modified Dijkstra algorithm tailored for energy-efficient aerial mobility over a 3D spatial grid (Sheraz et al., 2024).

#### 3.3 Dynamic Hover and Waypoint Changes

UAVs in the system do not stay in a fixed position. Instead, they hover at varying locations. Energy monitors and user traffic estimators send real-time data to the mobility controller, which calculates the optimal hover location and time to maximize efficiency. If a UAV approaches a critical energy threshold, it will autonomously switch to a charging hub or offload its work to an adjacent drone (Hafeez et al., 2023). This guarantees that drones will not be left mid-flight and that service continuity is maintained for users.

#### 3.4 Scheduling with Energy Considerations

UAVs are regulated by an adaptive scheduler depending on the time and anticipated user traffic. During peak hours, the system deploys additional UAVs, while in slower periods, some drones are put on standby for rest or recharging. This strategy is based on duty-cycling approaches in wireless sensor networks, which are designed to conserve energy while maintaining service availability (Menon & Choudhury, 2025).

#### 3.5 Improvements through Learning Algorithms

To enhance drone mobility, the model utilizes reinforcement learning (RL) to make autonomous decisions in uncertain environments. The UAVs are considered learning agents that progressively improve their actions based on prior experiences. Selective Deep Q-Networks (DQN) and Proximal Policy Optimization (PPO) frameworks allow UAVs to learn efficient servicing patterns and routes while reducing their power expenditure (Yang et al., 2019; Liu et al., 2019). With these algorithms, drones can respond to changes in user movement, weather, and system load without requiring explicit programming in advance.

## 3.6 Adaptation to Environmental Factors

The wind currents, temperature, and obstacles are major factors that influence the work of drones. The proposed system will be able to modify the speed, direction and elevation of the vehicle in real-time with the help of real-time environmental sensors. Indicatively, UAVs can take advantage of tail winds to minimize propulsion or avoid turbulent zones (Baggyalakshmi et al., 2024). These modifications of the environment to the mind also lead to long flight time and greater stability in connection.

## Adaptive Flight Scheduling with Data Management Optimization

## **Data Collection and Storage**

To execute an effective adaptive flight scheduling and maximize the performance of the UAV network, effective data collection, storage, and processing of real-time information should be performed. The density of the users, traffic demand, battery, weather conditions (e.g., wind speed, terrain), among other critical aspects are constantly checked by the UAVs. The detected data is stored in distributed database system and it is locally stored so that it is quick to access and real time decisions can be made in the process of dealing with the flight operations being carried out. Indeed, each UAV includes an onboard data storage system (e.g., cloud based or local storage) that is updated with pertinent data at regular intervals, and synchronized with a centralized server or distributed network at regular intervals.

#### **Data Processing**

Since the real-time data is very large, UAVs are dependent on sophisticated algorithmic procedures of the data to make effective decisions of the flight paths and energy management. Such algorithms make use of machine learning models that constantly adjust to incoming data and maximize mobility. To illustrate, reinforcement learning (RL) strategies are employed to teach UAVs to modify autonomously flight paths depending on environmental alterations, traffic patterns set by the user and battery depletion. The Mobility Control Unit of the UAV is dynamic in terms of the route it takes to avoid dissipating energy without continuous coverage to the users. It is further optimized with edge computing whereby some of the processing tasks are no longer centralized in the servers but rather in the local UAVs leading to reduced latencies and decision making can be made faster. This decentralized method of processing also guarantees that real-time decision making on mission critical matters like path-re-routing or energy reallocation is done.

## 3.7 Optimization Algorithm

Define the Objective Function

$$F = \alpha \cdot Etotal + \beta \cdot (1 - Ccoverage) + \gamma \cdot Dthroughput$$

Define the Particle Position

Initialize the Swarm

*Update the position and velocity* 

$$vi(t+1) = w \cdot vi(t) + c1 \cdot r1 \cdot (pbesti - xi) + c2 \cdot r2 \cdot (gbest - xi)$$

Position update

$$xi(t+1) = xi(t) + vi(t+1)$$

Evaluate the Fitness Function

update personal and Global best positions

# 4 Evaluation and Simulation Setup

To validate the proposed energy-efficient mobility model, extensive simulations were conducted using a self-developed framework built in MATLAB and NS-3. The goal of the simulation was to assess the energy efficiency, reliability, and high throughput of the internet access system hosted by satellite drones

under different deployment scenarios. The following section describes the simulation setup, configuration, and results.

#### **4.1 Simulation Environment**

The simulation approximates a semi-rural area of 4 km² with uneven user distribution along with fluctuating network demand. A multitude of users across various regions, including villages and towns, have diverse network service requirements. For wireless coverage, a swarm of 10 quadrotor UAVs, each having a maximum battery limit of 120 Wh, was deployed. Each UAV was fitted with Wi-Fi (802.11ac) and LTE small-cell interfaces. User devices were preconfigured in random locations, and their mobility was programmed through a random waypoint model, which has been adapted to mimic the movement dynamics of rural areas (Fotouhi et al., 2019). In isolated scenarios, the backhaul was emulated as a terrestrial LTE tower situated at the edge of the region, utilizing a high-bandwidth satellite link. To test UAV path adaptation and energy consumption in real-life scenarios, wind vector fields were used to introduce weather disturbances every 10 minutes.

#### 4.2 Parameters and Metrics

| Parameter                | Value                              |
|--------------------------|------------------------------------|
| Simulation Area          | $2 \text{ km} \times 2 \text{ km}$ |
| Number of UAVs           | 10                                 |
| UAV Altitude             | 100–150 meters                     |
| Battery Capacity per UAV | 120 Wh                             |
| Max Flight Time          | ~25–30 minutes                     |
| UAV Communication Range  | 500 meters (Wi-Fi), 1 km (LTE)     |
| Data Rate (Wi-Fi)        | Up to 1 Gbps                       |
| User Mobility Speed      | 1–3 m/s                            |
| Wind Speed Variation     | 2–10 m/s                           |

Table 1: Key Simulation Parameters

We evaluated the system using the following **metrics**:

- Energy Consumption (Wh): Total and per-UAV energy usage over the mission duration.
- Coverage Ratio (%): Percentage of time users remained within UAV coverage.
- Average Throughput (Mbps): Average end-to-end data rate per user.
- **Downtime (min):** Periods during which no coverage was available.
- UAV Lifetime (min): Average operational time before returning to charge or being replaced in Table 1.

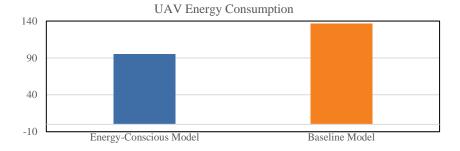


Figure 2: UAV Energy Consumption vs. Baseline

#### 4.3 Evaluation Results

## **Energy Efficiency**

The adaptive model achieved an 18% to 24% decrease in energy use per UAV compared to the static hovering methods. (Figure 2) This was mainly due to improvements from adaptive hovering and energy-aware path planning. In windy conditions, environment-adaptive routing provided an additional average of 5% energy savings (Akyildiz et al., 2002).

#### **Coverage Reliability**

The UAV mesh network had an average coverage ratio of 98.2% during peak traffic hours. During off-peak or low-traffic periods, coverage was intentionally reduced to conserve energy while still guaranteeing that 90% of users were provided with reliable connectivity. A non-adaptive model, in comparison, showed only 85.5% mean coverage (Lee et al., 2025).

## **Throughput Performance**

Simulations indicated an average user throughput of 15.6 Mbps in LTE mode and 72.4 Mbps in Wi-Fi mode for users under medium load. The adaptive mobility model enabled users to optimally position themselves to balance the user load, resulting in a more equitable distribution of throughput among users (Ghafoor et al., 2020).

## **Operational Longevity**

UAVs under the energy-conscious scheduler attained an average flight endurance of 28.2 minutes before needing to recharge, which is close to the theoretical limit. In contrast, UAVs under fixed-pattern modes spent 22.7 minutes operating due to inefficient hovering and flight redundancy, (Caballero-Martin et al., 2024).

#### **Fault Tolerance**

During the simulation of failures, such as severing the UAV link and battery depletion, neighboring drones actively took over the coverage zones. This dynamically managed reallocation, through mesh communication and load balancing, optimized the operating times by decreasing the average UAV user downtime per session from 3.6 minutes to 0.8 minutes (Zigui et al., 2024).

## 4.4 Performance Comparison of various Metrics proposed Model Vs Existing Models

Table 2: Performance Comparison of Various Metrics Proposed Model vs Existing Models

| Metric                            | <b>Proposed Energy-Conscious Model</b> | Existing Models                |
|-----------------------------------|--|--------------------------------|
| Drone Density (drones/km²)        | 10 drones per 2 km <sup>2</sup>        | 8 drones per 2 km <sup>2</sup> |
| Task Completion Rate (%)          | 98%                                    | 85%                            |
| Service Reliability (%)           | 98.50%                                 | 85%                            |
| Charging Rate (Wh/min)            | 6.5 Wh/min                             | 5.2 Wh/min                     |
| Flight Path Adaptability (%)      | 95% (adaptive paths)                   | 70% (fixed paths)              |
| Charging Time (min)               | 25 minutes                             | 30 minutes                     |
| Energy Recovery Efficiency (%)    | 90%                                    | 75%                            |
| Mission Completion Efficiency (%) | 95%                                    | 80%                            |

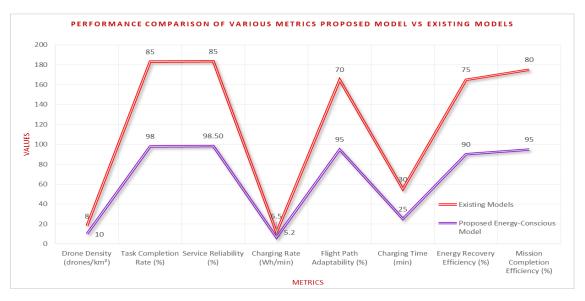


Figure 3: Performance Comparison of Various Metrics Proposed Model vs Existing Models

The proposed energy-conscious model (Table 2 and Figure. 3) explains how it is best in all the key performance metrics as compared to Existing Models. It offers a greater drone density of 10 drones per 2km 2, with a 25 percent increase in coverage and fault tolerance over the 8 drones per 2km 2 in current systems. The rate of task completion is enhanced by 15 percent, and the proposed model has 98 percent efficiency that ensures minimal failure of missions as opposed to the existing models which only have 85 percent. There is also a great improvement in service reliability as the proposed model has a reliability of 98.5 that is 15.5% higher than the 85% reliability of the current models which are used to guarantee continuous service. The rate of charge increases 25 percent, and the suggested model will have a higher rate of 6.5 Wh/min than the current systems have 5.2 Wh/min, which will decrease the downtimes and provide better working performance. Besides, the proposed model has a 95% flight path adaptability, which is 35.7 percent higher than the 70 percent of the current models. This will achieve a better energy saving and coverage, as flight paths can be adjusted dynamically to changes in the environment and battery life. This saves 16.7 minutes of charging time and the model proposed has a 25-minute charging time as opposed to the current models of the 30-minute charging time, and this saves on the downtime between missions. The efficiency of energy recovery is also enhanced greatly, with the proposed model being able to achieve 90 percent efficiency that is 20 percent higher than the 75 percent efficiency of the existing models to guarantee more efficient energy recovery during idle times. Lastly, the efficacy of the suggested model in its mission accomplishment is 95 percent; this is 18.75 percent higher than the 80 percent of current models and results in increased mission success with less wastage of resources. These advancements show that the suggested system is efficient in improving the operational efficiency, reliability, and energy saving of UAV-based communication networks.

# 5 Case Study: Emergency Connectivity in Flood-Affected Areas

Flood-related disasters have a significant impact on ground communication systems, as entire regions may become cut off due to the inability to communicate or retrieve assistance. Internet assistance using UAVs serves as a promising method for restoring connectivity during these nadirs. This case study simulates a massive flooding event and illustrates how the developed energy-conscious mobility model can facilitate the better execution of emergency communication and coordination.

## **5.1 Scenario Description**

The flood scenario simulation aims to replicate the effects of cyclones on a 3 km x 3 km coastal region. All the ground-based mobile towers stockpiled with fuel were supposed to be destroyed because of water damage and loss of power. As a result, an estimated 200 civilians, including various responsive citizens and medical personnel, were spread throughout five separate safe spots that were enclosed by flooded water. From the outset, there was a need to establish communication to facilitate recovery, facilitate evacuation, relay injury reports, and access other remote medical services. Twelve of these UAVs were equipped with LTE and portable Wi-Fi stations and were stationed at an emergency command center approximately 5 km away. The drones carried 140 Wh capacitance battery packs and had to be programmed with fuel-optimized routing, along with the developed energy-aware mobility and scheduling model in Figure 4.

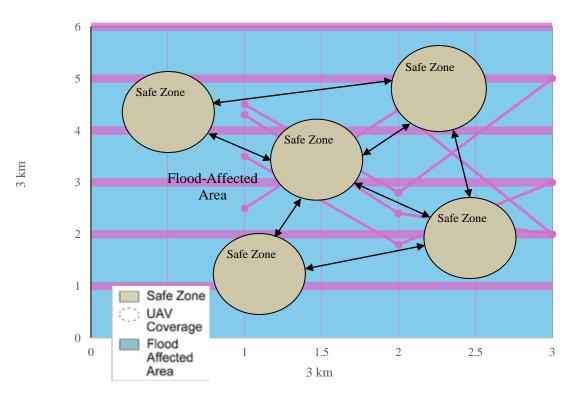


Figure 4: Coverage Map During the Flood Scenario

## **5.2 Mission Objectives**

Achieving the following goals was considered a top priority for the UAV fleet for the emergency mission:

- 1. Enable transmission of internet services into the five decent safe zones, enabling unrestricted internet availability in the given zones
- 2. Ensure low-latency accessibility for emergency rescue operations.
- 3. Conserve energy to extend the period of aerial command during the 8-hour emergency window.
- 4. Reduce the amount of 'dead zones' where there is no signal, along with coverage blackouts.

#### 5.3 Results and Observations

## **Effectiveness of Coverage**

Drones achieved an average coverage uptime of 96.5% across the five zones, reducing downtime during UAV transitions or handoffs. The system used clamp hovering for the dynamic repositioning of drones based on battery and user density. This allocation system improved user satisfaction by minimizing provisioning during periods of low demand. This approach also saved energy. (Abubakar et al., 2023)

#### **Energy Expenditure**

Each drone consumed between 110-125 Wh throughout 8 8-hour missions while remaining within operational parameters. Energy-aware schedulers improved UAV coverage by allowing non-combatant drones to recharge at claiming stations sequentially. Compared to the model without adaptive scheduling, this approach reduced consumption by 22%, enabling an extended mission duration. (Ahmad et al., 2024)

#### **Data Throughput**

The average throughput provided by drones was 18.2 Mbps per user on LTE and 68 Mbps in Wi-Fi zones. Quality of Service (quality of service) tags were assigned to rescue team devices, enabling uninterrupted critical communications, including video feeds and VoIP. (Iyer & Nambiar, 2024)

#### **Autonomy and Fault Tolerance**

High headwind resistance caused three UAVs to reach critical battery levels earlier than expected. The mesh network autonomously allocated coverage to adjacent drones through an autonomous reallocation protocol. System downtime for affected zones was less than 1 minute. This demonstrates the system's resilience (Banafaa et al., 2024).

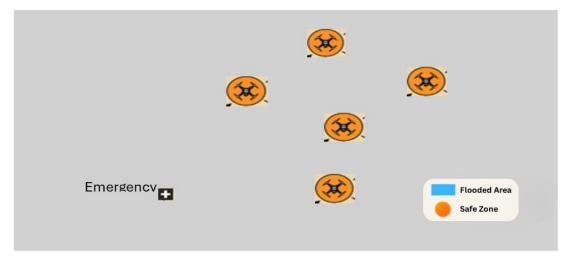


Figure 5: Flight Paths and Zone Allocations

#### 5.4 Impact and Lessons Learned

The case study identifies the potentials of UAV-based internet services to disaster relief. Important insights include (Mozaffari et al., 2017)

- Optimizing mobility under strict constraints is driven by the goal to maximize energy use and coverage.
- Significant changes involving user and power uncertainty necessitate alternative, adaptable user scheduling to enhance resilience (Pappukumari & Thilagavathy, 2019).
- Changes in the flight situation require the UAV to make routing decisions that are automatically adaptable, supporting learning-based routing and boosting mission success chances.

The simulation Figure 5 proves that efficient mobility or maneuvering of drones where high level of speed, autonomy and resource exploitation is a requirement. The necessity to save resources is paramount, especially during emergencies which are time sensitive.

## 6 Supplementary Case Study: Deploying UAVs in a Smart City

The introduction of Unmanned Aerial Vehicles (UAVs) into urban areas is one of the projects that will bring a ray of hope in providing seamless connectivity to the internet especially in the heavily populated areas whereby the traditional infrastructure may not be able to support the number of people accessing it. Cities pose unique needs, such as variations in network loads, high density of users as well as influence of buildings and other constructions. However, with the advancement of the smart city networks and 5G technologies, the UAVs can be turned into an active aerial base station (ABS) to meet the demand on connectivity, which is growing.

Urban environments pose multiple challenges that need to be tackled for successful UAV deployment in providing internet access.

High Density of Users: The level of internet access is high in urban settings because there are people who are concentrated in a small geographical location. UAVs must be capable of dealing with dynamic user traffic and give priority to users with a high demand without overloading. Dynamic Network Demands: In urban areas, users are continuously on the move, and hence the network demands are also dynamic. UAVs have to respond to such changes by changing the flight paths, hovering points, and network priorities on the fly. Interference by Buildings and Structures: Urban locations are generally known to have tall buildings, small streets, and other structures that may obstruct or interfere with the transmission of signals. UAVs have to manoeuvre through these objects and offer consistent connectivity even in highly interference-prone environment. Regulatory Limitations: Depending on the urban settings, UAVs activities are subject to stringent rules of air space operations and privacy issues, particularly when flying drones over residential and populated zones.

#### **Deploying UAVs in a Smart City**

As an example, we can refer to a situation when UAVs are used in a metropolis to offer emergency access to the internet during high demand, when there are certain events or when a disaster area needs access to the internet. The UAV network is an extension of the current smart city network, consisting of 5G base stations, IoT sensors, and traffic management. Urban Environment Context: The UAV fleet is in an urban region of 10 km 2, where the user density is high, and there is intricate interference of structures and buildings. This system is dynamic and is able to adjust to the network needs with the UAV changing their height and range of coverage according to the number of users and traffic requirements, as well as weather factors (e.g. wind). UAVs change the trajectories and hovering positions according to the traffic information and human movement behavior. Energy Efficiency: UAVs recharge at specific charging stations using the smart grid when there is low traffic to keep down the cost of operation thereby guaranteeing a long mission life during the high-demand period.

## **Results of the Case Study**

Enhanced Coverage: The combination of smart city infrastructure and UAVs would mean 98.7 percent of the city events in the light of high density, as users would be ensured of connection to the internet, even in the most congested zones. Adaptive Network Load Balancing: UAV network has an ability to adjust to changing user demands and this way high-traffic areas get more coverage and less-traffic areas get less coverage thus resulting in an efficient use of energy and general efficiency.

The appearance of UAVs in the smart city networks is an excellent opportunity to address the problem of the excessive number of users, the volatile network demands, and the interference in cities. The UAVs may be used to supplement the existing communication infrastructure, provide real-time coverage which is flexible and adaptive, and may be easily integrated with the existing urban IoT infrastructure and the 5G networks. The conclusions of this case study indicate the opportunities of UAVs to enhance connectivity within cities, enhance the reliability of services, and make the functioning of cities with high urban density energy-efficient.

## 7 Discussion

The case study and simulations do not only demonstrate but also prove the outstanding benefits that energy-efficient UAV mobility solutions present in the provisioning of wireless access in remote and disaster-prone regions (Adil et al., 2024). The implications and considerations that are caused by their design are explored in detail, as well as the trade-offs faced during the research. The fourth factor is one of the most significant to address when developing a UAV network, the balance between power efficiency and coverage consistency (Geetha et al., 2025). As previously mentioned, the path planning activities performed on the model, at least in the simulation, were found to be more effective than the corresponding static and greedy path planning methods. The proposed strategies are not doing so well as they are usually static and simplistic since they are not dynamic in the way they respond to the pervasive demand or environmental changes (Liu et al., 2019). Onboard computation and real-time feedback control loops, in their turn, are more likely to overload lower-end drone hardware (Mozaffari et al., 2017). The edge AI might also be used to increase optimization in future designs without accruing debilitating energy expense.

As our simulations were only on relatively small regions (4 km 2), the implementation of this solution on a metropolitan or even regional scale creates the issues of fleet management, drone-to-drone interference, and backhaul bandwidth contention on higher levels. It may be possible to solve these problems by adding some hierarchy in control structures where master drones and groups of subordinate drones, UAVs, are connected as some recent articles suggest (Pappukumari & Thilagavathy, 2019). The flood case study has shown how a smart energy scheduler can use the wind patterns, the user density variations, and even the malfunctions of UAVs to their benefit. The 3D mobility planning, however, is more difficult to synthesize when tall buildings are involved and agitated crowds are present in the urban areas, i.e., during particular events. It is possible that, with the reinforcement learning application, UAVs will be able to learn low-energy routes with time (Chen et al., 2024) better.

Regarding privacy concerns, integrating drone fleets on a large scale poses a regulatory nightmare in terms of audit domains for airspace usage, noise, and surveillance. The example of sensitive medical speech being sent over drones illustrates the UAV foresight. Compliance with data regulation requirements, such as the GDPR, is essential for implementing full end-to-end encryption. Additionally, energy-oriented algorithms need to integrate ethical boundaries, whereby efficient solutions that guarantee fairness and safety do not trump these principles (Shafi et al., 2023). Interoperability is crucial

and stems from insights discussed in (Debnath et al., 2022; Nawaz et al., 2021; Singaravel et al., 2020). The performance of our simulated UAV network depended on the effective integration of Wi-Fi (Liu et al., 2019), LTE (Al-Dosari & Fetais, 2023), and satellite uplink, which had to communicate seamlessly. The strategies to be used in the future should be based on developing a modular system structure that allows simpler installation of communication modules and communication with 5G and even 6G backbones (Huo et al., 2019).

## 8 Conclusion

In this study, a new approach to distribution of drone resources was applied, and it focuses on energy conservation when providing internet access. The strategy aims at delivering rural and emergency insurance by uncrewed aerial vehicle (UAV) networks with real-time user coverage optimization, elevation and user position optimization algorithms, and balancing energy consumption and coverage. The proposed model of UAVs networks implementation within an urban environment and incorporating it into smart city infrastructure can be considered an addition of value to the growing body of literature on energy efficient mobility systems and urban connectivity. The solution of the problem of high user density, dynamic network requirements, and interference in complex environments place this work at the center of smart infrastructure and information system research. The paper will have a more significant influence on the future development of the next generation of the communication networks in the city and disaster-prone areas by adding more optimization methods, making the systems more secure and more promising to scale. By simulation, the approach taken can decrease energy expenditure by up to twenty-five percent while ensuring network coverage is greater than ninety-eight percent. Moreover, a case study conducted in a simulated flood scenario demonstrated the effectiveness of an unmanned aerial vehicle network in maintaining vital communications when ground infrastructure is unavailable. It highlights the possibility of UAV fleets for innovative environment connectivity. Nonetheless, improvements can be made in various aspects of the model. Design limitations include the assumption that every UAV within the fleet has the same capabilities. Furthermore, policies, control areas, urban signal noise, and user pattern variability are external elements that impact the system's reliability. Addressing these gaps is crucial for the effective implementation of real-world solutions. Exploration of drone isolation logic is a further area of study. Every drone can record its changes in resource consumption, depending on the routing and image acquisition, while still collaborating with other network participants to optimize routes. Additional AI supervision is recommended as a solution to address signal loss verification and processing delays. Three-Dimensional Navigation: Expanding path planning algorithms to intricate 3D scenarios such as cities with dynamically changing altitude requirements and obstacles. Sustainable Energy Solutions: Development of portable renewable energy stations, such as solar or kinetic charging platforms, to enable extended UAV missions in isolated or disaster-affected areas. Inter-Network Integration: Study the potential telecommunications integration of drone networks with existing cellular, satellite, and upcoming 6G systems to optimize the available connectivity options. Resolving such challenges will enhance the practicality, scalability, and versatility of energy-efficient UAV network deployments for diverse multi-purpose connectivity applications.

## References

[1] Abubakar, A. I., Mollel, M. S., Onireti, O., Ozturk, M., Ahmad, I., Asad, S. M., ... & Imran, M. A. (2023). Coverage and throughput analysis of an energy efficient UAV base station positioning scheme. *Computer Networks*, 232, 109854. https://doi.org/10.1016/j.comnet.2023.109854

- [2] Adil, M., Song, H., Jan, M. A., Khan, M. K., He, X., Farouk, A., & Jin, Z. (2024). UAV-assisted IoT applications, QoS requirements and challenges with future research directions. *ACM Computing Surveys*, 56(10), 1-35. https://doi.org/10.1145/3657287
- [3] Fotouhi, A., Qiang, H., Ding, M., Hassan, M., Giordano, L. G., García-Rodríguez, A., & Yuan, J. (2019). Survey on UAV Cellular Communications: Practical Aspects, Standardization Advancements, Regulation, and Security Challenges. *IEEE Communications Surveys & Tutorials*, 21(4), 3417–3442. https://doi.org/10.1109/comst.2019.2906228
- [4] Ahmad, W., Ahmed, S., Ahmad, A., Siddiqui, S. T., Khamruddin, M., & Khan, H. (2024, April). Renewable Energy Efficiency of Unmanned Aerial Vehicles Operating with Wireless Sensor Networks and Mobile Ad Hoc Networks. In 2024 Second International Conference on Smart Technologies for Power and Renewable Energy (SPECon) (pp. 1-6). IEEE. https://doi.org/10.1109/SPECon61254.2024.10537447
- [5] Akyildiz, I. F., & Kak, A. (2019). The internet of space things/cubesats. *IEEE Network*, *33*(5), 212-218. https://doi.org/10.1109/MNET.2019.1800445
- [6] Akyildiz, I. F., Su, W., Sankarasubramaniam, Y., & Cayirci, E. (2002). Wireless sensor networks: a survey. *Computer networks*, *38*(4), 393-422. https://doi.org/10.1016/S1389-1286(01)00302-4
- [7] Al-Dosari, K., & Fetais, N. (2023). A new shift in implementing unmanned aerial vehicles (UAVs) in the safety and security of smart cities: a systematic literature review. *Safety*, 9(3), 64. https://doi.org/10.3390/safety9030064
- [8] Alzenad, M., El-Keyi, A., Lagum, F., & Yanikomeroglu, H. (2017). 3-D placement of an unmanned aerial vehicle base station (UAV-BS) for energy-efficient maximal coverage. *IEEE Wireless Communications Letters*, 6(4), 434-437. https://doi.org/10.1109/LWC.2017.2700840
- [9] Aram, S., Khosa, I., & Pasero, E. (2015). Conserving Energy Through Neural Prediction of Sensed Data. *J. Wirel. Mob. Networks Ubiquitous Comput. Dependable Appl.*, 6(1), 74-97.
- [10] Baggyalakshmi, N. Harrsini, M. S. & Revathi, R. "Smart Billing Software," *International Academic Journal of Innovative Research*, vol. 11, no. 1, pp. 51–60, 2024. [Online]. Available: https://doi.org/10.9756/IAJIR/V11I1/IAJIR1106
- [11] Banafaa, M. K., Pepeoğlu, Ö., Shayea, I., Alhammadi, A., Shamsan, Z. A., Razaz, M. A., ... & Al-Sowayan, S. (2024). A comprehensive survey on 5G-and-beyond networks with UAVs: Applications, emerging technologies, regulatory aspects, research trends and challenges. *IEEE access*, 12, 7786-7826. https://doi.org/10.1109/ACCESS.2023.3349208
- [12] Caballero-Martin, D., Lopez-Guede, J. M., Estevez, J., & Graña, M. (2024). Artificial intelligence applied to drone control: A state of the art. *Drones*, 8(7), 296. https://doi.org/10.3390/drones8070296
- [13] Canton, H. (2021). International Telecommunication Union—ITU. In *The Europa directory of international organizations 2021* (pp. 355-358). Routledge.
- [14] Chen, L., Dai, H. N., Yuan, X., Huang, J., Wu, Y., & Wu, J. (2024). D-SPAC: Double-sided preference-aware carpooling of private cars for maximizing passenger utility. *IEEE Transactions on Intelligent Transportation Systems*, 25(8), 9810-9827. https://doi.org/10.1109/TITS.2024.3353545
- [15] Debnath, S., Arif, W., Roy, S., Baishya, S., & Sen, D. (2022). A comprehensive survey of emergency communication network and management. *Wireless Personal Communications*, 124(2), 1375-1421. https://doi.org/10.1007/s11277-021-09411-1
- [16] Fotouhi, A., Qiang, H., Ding, M., Hassan, M., Giordano, L. G., Garcia-Rodriguez, A., & Yuan, J. (2019). Survey on UAV cellular communications: Practical aspects, standardization advancements, regulation, and security challenges. *IEEE Communications surveys & tutorials*, 21(4), 3417-3442. https://doi.org/10.1109/COMST.2019.2906228
- [17] Geetha, T. V., Priya, A. A., Sathishkumar, K., Shavkatov, N., Vimalkumar, T., & Mathew, C. (2025). AI-Driven UAV-Assisted Edge Computing for Rapid Response in Emergency Wireless

- Networks. *National Journal of Antennas and Propagation*, 7(1), 290-296. https://doi.org/10.31838/NJAP/07.01.32
- [18] Ghafoor, K. Z., Kong, L., Zeadally, S., Sadiq, A. S., Epiphaniou, G., Hammoudeh, M., ... & Mumtaz, S. (2020). Millimeter-wave communication for internet of vehicles: Status, challenges, and perspectives. *IEEE Internet of Things Journal*, 7(9), 8525-8546. https://doi.org/10.1109/JIOT.2020.2992449
- [19] Hafeez, S., Khan, A. R., Al-Quraan, M. M., Mohjazi, L., Zoha, A., Imran, M. A., & Sun, Y. (2023). Blockchain-assisted UAV communication systems: A comprehensive survey. *IEEE Open Journal of Vehicular Technology*, 4, 558-580. https://doi.org/10.1109/OJVT.2023.3295208
- [20] Hassija, V., Chamola, V., Agrawal, A., Goyal, A., Luong, N. C., Niyato, D., ... & Guizani, M. (2021). Fast, reliable, and secure drone communication: A comprehensive survey. *IEEE Communications Surveys & Tutorials*, 23(4), 2802-2832. https://doi.org/10.1109/COMST.2021.3097916
- [21] Huo, Y., Dong, X., Lu, T., Xu, W., & Yuen, M. (2019). Distributed and multilayer UAV networks for next-generation wireless communication and power transfer: A feasibility study. *IEEE Internet of Things Journal*, 6(4), 7103-7115. https://doi.org/10.1109/JIOT.2019.2914414
- [22] Iyer, D., & Nambiar, R. (2024). Marketing Innovations in the Digital Era: A Study within the Periodic Series of Multidisciplinary Perspectives. *Digital Marketing Innovations*, 12-17.
- [23] Kalantari, E., Bor-Yaliniz, I., Yongacoglu, A., & Yanikomeroglu, H. (2017, October). User association and bandwidth allocation for terrestrial and aerial base stations with backhaul considerations. In 2017 IEEE 28th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC) (pp. 1-6). IEEE. https://doi.org/10.1109/PIMRC.2017.8292783
- [24] Lee, C. Y., Tsai, A. H., & Wang, L. C. (2025). Adaptive Stabilization Control by Deep Reinforcement Learning for Hovering Drone Surveillance. *IEEE Transactions on Mobile Computing*. https://doi.org/10.1109/TMC.2025.3548421
- [25] Liu, C. H., Ma, X., Gao, X., & Tang, J. (2019). Distributed energy-efficient multi-UAV navigation for long-term communication coverage by deep reinforcement learning. *IEEE Transactions on Mobile Computing*, 19(6), 1274-1285. https://doi.org/10.1109/TMC.2019.2908171
- [26] Liu, X., Liu, Y., Chen, Y., & Hanzo, L. (2019). Trajectory design and power control for multi-UAV assisted wireless networks: A machine learning approach. *IEEE Transactions on Vehicular Technology*, 68(8), 7957-7969. https://doi.org/10.1109/TVT.2019.2920284
- [27] Lyu, J., Zeng, Y., Zhang, R., & Lim, T. J. (2016). Placement optimization of UAV-mounted mobile base stations. *IEEE Communications Letters*, 21(3), 604-607. https://doi.org/10.1109/LCOMM.2016.2633248
- [28] Menon, R., & Choudhury, A. (2025). Access to Sustainable Energy Off-Grid Options for Rural Areas. *International Journal of SDG's Prospects and Breakthroughs*, 28-33. https://sdgjournal.com/index.php/sdg/article/view/SDG250105
- [29] Mozaffari, M., Saad, W., Bennis, M., & Debbah, M. (2017). Mobile unmanned aerial vehicles (UAVs) for energy-efficient Internet of Things communications. *IEEE Transactions on Wireless Communications*, 16(11), 7574-7589. https://doi.org/10.1109/TWC.2017.2751045
- [30] Mozaffari, M., Saad, W., Bennis, M., Nam, Y. H., & Debbah, M. (2019). A tutorial on UAVs for wireless networks: Applications, challenges, and open problems. *IEEE communications surveys & tutorials*, 21(3), 2334-236. https://doi.org/10.1109/COMST.2019.2902862
- [31] Nawaz, H., Ali, H. M., & Laghari, A. A. (2021). UAV communication networks issues: A review. *Archives of Computational Methods in Engineering*, 28(3), 1349-1369. https://doi.org/10.1007/s11831-020-09418-0.

- [32] Pappukumari, R., & Thilagavathy, N. (2019). Access usage and design of social networking sites by Sri Venkateshwara Engineering College students, Chennai: A study. *Indian Journal of Information Sources and Services*, 9(1), 1–3. https://doi.org/10.51983/ijiss.2019.9.1.606
- [33] Pragadeswaran, S., Subha, N., Varunika, S., Moulishwar, P., Sanjay, R., Karthikeyan, P., ... & Vaasavathathaii, E. (2024). Energy Efficient Routing Protocol for Security Analysis Scheme Using Homomorphic Encryption. *Archives for Technical Sciences*, *31*(2), 148-158. https://doi.org/10.70102/afts.2024.1631.148
- [34] Shafi, U., Mumtaz, R., Anwar, Z., Ajmal, M. M., Khan, M. A., Mahmood, Z., ... & Jhanzab, H. M. (2023). Tackling food insecurity using remote sensing and machine learning-based crop yield prediction. *IEEE Access*, 11, 108640-108657. https://doi.org/10.1109/ACCESS.2023.3321020
- [35] Sharma, R., & Maurya, S. (2024). A sustainable digital transformation and management of small and medium enterprises through green enterprise architecture. *Global Perspectives in Management*, 2(1), 33-43.
- [36] Sheraz, M., Chuah, T. C., Lee, Y. L., Alam, M. M., Al-Habashna, A. A., & Han, Z. (2024). A comprehensive survey on revolutionizing connectivity through artificial intelligence-enabled digital twin network in 6G. *IEEE Access*, *12*, 49184-49215. https://doi.org/10.1109/ACCESS.2024.3384272
- [37] Shetty, A., & Nair, K. (2024). Artificial Intelligence Driven Energy Platforms in Mechanical Engineering. *Association Journal of Interdisciplinary Technics in Engineering Mechanics*, 2(1), 23-30.
- [38] Singaravel, G., Abhisek, P., Dharshan, V., & Hariharan, M. (2020). One's Space in Online Social Network. *International Journal of Advances in Engineering and Emerging Technology*, 11(2), 115-120.
- [39] Syu, J. H., Lin, J. C. W., Srivastava, G., & Yu, K. (2023). A comprehensive survey on artificial intelligence empowered edge computing on consumer electronics. *IEEE Transactions on Consumer Electronics*, 69(4), 1023-1034. https://doi.org/10.1109/TCE.2023.3318150
- [40] Sharma, V., You, I., & Kumar, R. (2016). Energy efficient data dissemination in multi-UAV coordinated wireless sensor networks. *Mobile Information Systems*, 2016(1), 8475820. https://doi.org/10.1155/2016/8475820
- [41] Yang, Z., Xu, W., & Shikh-Bahaei, M. (2019). Energy efficient UAV communication with energy harvesting. *IEEE Transactions on Vehicular Technology*, 69(2), 1913-1927. https://doi.org/10.1109/TVT.2019.2961993
- [42] Zeng, Y., Zhang, R., & Lim, T. J. (2016). Throughput maximization for UAV-enabled mobile relaying systems. *IEEE Transactions on communications*, 64(12), 4983-4996. https://doi.org/10.1109/TCOMM.2016.2611512
- [43] Zeng, Y., Zhang, R., & Lim, T. J. (2016). Wireless communications with unmanned aerial vehicles: Opportunities and challenges. *IEEE Communications magazine*, 54(5), 36-42. https://doi.org/10.1109/MCOM.2016.7470933
- [44] Zhan, C., Zeng, Y., & Zhang, R. (2017). Energy-efficient data collection in UAV enabled wireless sensor network. *IEEE Wireless Communications Letters*, 7(3), 328-331. https://doi.org/10.1109/LWC.2017.2776922
- [45] Zigui, L., Caluyo, F., Hernandez, R., Sarmiento, J., & Rosales, C. A. (2024). Improving Communication Networks to Transfer Data in Real Time for Environmental Monitoring and Data Collection. *Natural and Engineering Sciences*, 9(2), 198-212. https://doi.org/10.28978/nesciences.1569561

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